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5 Two-Way Crossed Classification

Days to first germination of three varieties of ca
rot seed grown in two types of potting soil.

Soil Tpye	Variety 1	Variety 2	Variety 3
1	$y_{111} = 6$	$y_{121} = 13$	$y_{131} = 14$
	$y_{112} = 10$	$y_{122} = 15$	$y_{132} = 22$
	$y_{113} = 11$		
2	$y_{211} = 12$	$y_{221} = 31$	$y_{231} = 18$
	$y_{212} = 15$		$y_{232} = 9$
	$y_{213} = 19$		$y_{233} = 12$
	$y_{214} = 18$		

This might be called "an unbalanced factorial ex
periment".

Sample sizes:

Soil type	Variety 1	Variety 2	Variety 3
1	$n_{11}=3$	$n_{12}=2$	$n_{13}=2$
2	$n_{21}=4$	$n_{22}=1$	$n_{23}=3$

In general we have

$i=1,2,\ldots,a$ levels for the first factor

$j=1,2,\ldots,b$ levels for the second factor

$n_{ij}>0$ observations at the i-th level of the first factor and the j-th level of the second factor

We will restrict our attention to normal-theory Gauss-Markov models.

5.1 "Cell Means" Model

$$y_{ijk}=\mu_{ij}+\epsilon_{ijk}$$

where

$$\epsilon_{ijk}\sim NID(0,\sigma^2)\quad\begin{cases} i=1,\ldots,a\\ j=1,\ldots,b\\ k=1,\ldots,n_{ij}\end{cases}$$

Clearly, $E(y_{ijk})=\mu_{ij}$ is estimable if $n_{ij}>0$.

Overall mean response:

Mean response at i-th level of factor 1, averaging across the levels of factor 2.

Mean response at j-th level of factor 2, averaging across the levels of factor 1

Contrasts of interest:
"main effects" for factor 1:

"main effects" for factor 2:

Conditional effects:

Interaction contrasts:

All of these contrasts are **estimable** when

$$n_{ij} > 0 \quad \text{for all } (i, j)$$

because

- $E(\bar{y}_{ij.}) = \mu_{ij}$
- Any linear function of estimable functions is estimable

5.2 An “Effects” Model

$$y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \epsilon_{ij}$$

where

$$\begin{aligned} \epsilon_{ijk} &\sim NID(0, \sigma^2) \\ i &= 1, 2, \ldots, a \\ j &= 1, 2, \ldots, b \\ k &= 1, 2, \ldots, n_{ij} > 0 \end{aligned}$$

$$\begin{bmatrix} y_{111} \\ y_{112} \\ y_{113} \\ y_{121} \\ y_{122} \\ y_{131} \\ y_{132} \\ y_{211} \\ y_{212} \\ y_{213} \\ y_{214} \\ y_{221} \\ y_{231} \\ y_{232} \\ y_{233} \end{bmatrix} = \begin{bmatrix} 1&1&0&1&0&0&1&0&0&0&0&0 \\ 1&1&0&1&0&0&1&0&0&0&0&0 \\ 1&1&0&1&0&0&1&0&0&0&0&0 \\ 1&1&0&0&1&0&0&1&0&0&0&0 \\ 1&1&0&0&1&0&0&1&0&0&0&0 \\ 1&1&0&0&0&1&0&0&1&0&0&0 \\ 1&1&0&0&0&1&0&0&1&0&0&0 \\ 1&0&1&1&0&0&0&0&0&1&0&0 \\ 1&0&1&1&0&0&0&0&0&1&0&0 \\ 1&0&1&1&0&0&0&0&0&1&0&0 \\ 1&0&1&1&0&0&0&0&0&1&0&0 \\ 1&0&1&0&1&0&0&0&0&0&1&0 \\ 1&0&1&0&0&1&0&0&0&0&0&1 \\ 1&0&1&0&0&1&0&0&0&0&0&1 \\ 1&0&1&0&0&1&0&0&0&0&0&1 \end{bmatrix} \begin{bmatrix} \mu \\ \alpha_1 \\ \alpha_2 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \gamma_{11} \\ \gamma_{12} \\ \gamma_{13} \\ \gamma_{21} \\ \gamma_{22} \\ \gamma_{23} \end{bmatrix} + \boldsymbol{\epsilon}$$

5.2.1 Baseline Restrictions

The resulting restricted model is

$$y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \epsilon_{ijk}$$

where

$$\epsilon_{ijk} \sim NID(0, \sigma^2) \quad \begin{cases} i = 1, \ldots, a \\ j = 1, \ldots, b \\ k = 1, \ldots, n_{ij} \end{cases}$$

and

$$\begin{aligned} \alpha_a &= 0 \\ \beta_b &= 0 \\ \gamma_{ib} &= 0 \;\text{ for all }\; i = 1, \ldots, a \\ \gamma_{aj} &= 0 \;\text{ for all }\; j = 1, \ldots, b \end{aligned}$$

We will call these the “baseline” restrictions.

Soil Type	Variety 1	Variety 2	Variety 3	Soil Type Means
1	$\mu_{11} = \mu + \alpha_1 + \beta_1 + \gamma_{11}$	$\mu_{12} = \mu + \alpha_1 + \beta_2 + \gamma_{12}$	$\mu_{13} = \mu + \alpha_1$	$\mu + \alpha_1 + \frac{\beta_1+\beta_2}{3} + \frac{\gamma_{11}+\gamma_{12}}{3}$
2	$\mu_{21} = \mu + \beta_1$	$\mu_{22} = \mu + \beta_2$	$\mu_{23} = \mu$	$\mu + \frac{\beta_1+\beta_2}{3}$
Var. means	$\mu + \frac{\alpha_1}{2} + \beta_1 + \frac{\gamma_{11}}{2}$	$\mu + \frac{\alpha_1}{2} + \beta_2 + \frac{\gamma_{12}}{2}$	$\mu + \frac{\alpha_1}{2}$	

Interpretation:

$\mu =$

$\alpha_i =$

$\beta_j =$

$\gamma_{ij} =$

Matrix formulation:

Least squares estimation:

Comments:

Imposing a set of restrictions on the paramete
in the "effects" model

$$y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \epsilon_{ijk}$$

to obtain a model matrix with full column ran

(i) Avoids the use of a generalized inverse in lea squares estimation.

(ii) Is equivalent to choosing a generalized invers for $\mathbf{b} = (\mathbf{X}^T\mathbf{X})^{-}\mathbf{X}^T\mathbf{y}$ in the unrestricted "e fects" model.

(iii) Restrictions must involve "non-estimable" qu tities for the unrestricted "effects" model.

(iv) Baseline restrictions using by SAS are
$\alpha_a = 0 \quad \beta_b = 0$
$\gamma_{ib} = 0$ for all $i = 1, \ldots, a$
$\gamma_{aj} = 0$ for all $j = 1, \ldots, b$

(v) Baseline restrictions using by R are
$\alpha_1 = 0 \quad \beta_1 = 0$
$\gamma_{i1} = 0$ for all $i = 1, \ldots, a$
$\gamma_{1j} = 0$ for all $j = 1, \ldots, b$

5.2.2 Σ-Restrictions

$$y_{ijk} = \omega + \gamma_i + \delta_j + \eta_{ij} + \epsilon_{ijk}$$

$$\mu_{ij} = E(y_{ijk})$$

where

$$\epsilon_{ijk} \sim NID(0, \sigma^2) \text{ and } \sum_{i=1}^{a} \gamma_i = 0 \quad \sum_{j=1}^{b} \delta_j = 0$$

$$\sum_{i=1}^{a} \eta_{ij} = 0 \quad \text{for each } j = 1, \ldots, b$$

$$\sum_{j=1}^{b} \eta_{ij} = 0 \quad \text{for each } i = 1, \ldots, a$$

Interpretation:

$\omega =$

$\delta_j - \delta_k =$

Similarly,

$\gamma_1 - \gamma_2 =$

For a model that includes the Σ-restrictions:

$\eta_{ij} =$

Matrix formulation:

Least squares estimation:

If restrictions are placed on "non-estimable" functions of parameters in the unrestricted "effects" model, then

- The resulting models are reparameterizations of each other.
- $\hat{\mathbf{y}} = P_{\mathbf{X}}\mathbf{y}$

  $\mathbf{e} = \mathbf{y} - \hat{\mathbf{y}} = (I - P_{\mathbf{X}})\mathbf{y}$

  $SSE = \mathbf{e}^T\mathbf{e} = \mathbf{y}^T(I - P_{\mathbf{X}})\mathbf{y}$

  $\hat{\mathbf{y}}^T\hat{\mathbf{y}} = \mathbf{y}^T P_{\mathbf{X}}\mathbf{y}$

  $SS_{\text{model}} = \mathbf{y}^T(P_{\mathbf{X}} - P_{\mathbf{1}})\mathbf{y}$

  are the same for any set of restrictions.
- The solution to the normal equations

  $$\mathbf{b} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y}$$

  and interpretations of the corresponding parameters will not be the same for all such sets of restrictions.

If you were to place restrictions on estimable func tions of parameters in

$$y_{ijk} = \mu + \alpha_1 + \beta_j + \gamma_{ij} + \epsilon_{ijk}$$

then you would change

- rank($\mathbf{X}$)
- space spanned by the columns of $\mathbf{X}$
- $\hat{\mathbf{y}} = \mathbf{X}(\mathbf{X}^T\mathbf{X})^-\mathbf{X}^T\mathbf{y}$ and OLS estimators of other estimable quantities.

Example 1.

In a study to examine the effect of temperature on percent shrinkage in dyeing fabrics was made on two replications for each of four fabrics in a complete randomized design. The data are the percent shrinkage of two replication fabric pieces dried at each of the four temperatures.

	Temperature			
Fabric	210°	215°	220°	225°
1	1.8,2.1	2.0,2.1	4.6, 5.0	7.5, 7.9
2	2.2, 2.4	4.2, 4.0	5.4, 5.6	9.8, 9.2
3	2.8, 3.2	4.4, 4.8	8.7, 8.4	13.2, 13.0
4	3.2, 3.6	3.3, 3.5	5.7, 5.8	10.9, 11.1

Consider the model $y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \epsilon_{ijk}$ where $\epsilon_{ijk} \sim NID(0, \sigma^2)$ and y_{ijk} denotes the percent shrinkage in dyeing fabric for the $k-$th fabric piece given the $j-$th temperature with the $i-$th fabric.

1. Note that the application of the lm() function in R imposes some restrictions to solve the normal equations. What are the restrictions?

2. Give an interpretation of α_4, $\alpha_2 - \alpha_4$ and γ_2 with respect to the restricted model and th mean change in systolic blood pressure.

3. The effects model under the R baseline restric tion has parameter vector for mean response

$$\boldsymbol{\delta} = (\mu.\alpha_2, \alpha_3, \alpha_4, \beta_2, \beta_3, \beta_4, \gamma_{22}, \gamma_{23}, \gamma_{24}, \gamma_3$$

(a) Determine a matrix $\mathbf{C}$ so that the testabl hypothesis $H_0 : \mathbf{C}\boldsymbol{\delta} = 0$ is the hypothes $H_0 : \mu_{.1} = \mu_{.2} = \mu_{.3} = \mu_{.4}$ where $\mu_{.j} =$ $\frac{1}{4}\sum_{i=1}^{4} \mu_{ij}$.

(b) Determine a matrix $\mathbf{C}$ so that the testabl hypothesis $H_0 : \mathbf{C}\boldsymbol{\delta} = 0$ is the hypothes $H_0 : \mu_{1.} = \mu_{2.} = \mu_{3.} = \mu_{4.}$ where $\mu_{i.}$ $\frac{1}{3}\sum_{j=1}^{3} \mu_{ij}$.

5.3 Normal Theory Gauss-Markov Model

$$y_{ijk} = \mu + \alpha_i + \beta_j + \gamma_{ij} + \epsilon_{ijk}$$

5.3.1 Analysis of Variance

$$\begin{aligned}
\mathbf{y}^T\mathbf{y} &= \mathbf{y}^T P_\mu \mathbf{y} + \mathbf{y}^T (P_{\mu,\alpha} - P_\mu)\mathbf{y} \\
&\quad + \mathbf{y}^T (P_{\mu,\alpha,\beta} - P_{\mu,\alpha})\mathbf{y} \\
&\quad + \mathbf{y}^T (P_{\mathbf{X}} - P_{\mu,\alpha,\beta})\mathbf{y} \\
&\quad + \mathbf{y}^T (I - P_{\mathbf{X}})\mathbf{y} \\
&= R(\mu) + R(\boldsymbol{\alpha}|\mu) + R(\boldsymbol{\beta}|\mu, \alpha) \\
&\quad + R(\boldsymbol{\gamma}|\mu, \boldsymbol{\alpha}, \boldsymbol{\beta}) + SSE
\end{aligned}$$

By Cochran's Theorem, these quadratic forms (or sums of squares) have independent chi-square distributions with 1, $a-1$, $b-1$, $(a-1)(b-1)$, and $n_{\bullet\bullet} - ab$ degrees of freedom, respectively, (if $n_{ij} > 0$ for all (i, j))

$$\begin{bmatrix} y_{111} \\ y_{112} \\ y_{113} \\ y_{121} \\ y_{122} \\ y_{131} \\ y_{132} \\ y_{211} \\ y_{212} \\ y_{213} \\ y_{214} \\ y_{221} \\ y_{231} \\ y_{232} \\ y_{233} \end{bmatrix} = \left[\begin{array}{c|cc|ccc|cccccc}
1 & 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\
1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\
1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\
1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1
\end{array}\right] \begin{bmatrix} \mu \\ \alpha_1 \\ \alpha_2 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \gamma_{11} \\ \gamma_{12} \\ \gamma_{13} \\ \gamma_{21} \\ \gamma_{22} \\ \gamma_{23} \end{bmatrix} + \boldsymbol{\epsilon}$$

call this $\mathbf{X}_\mu$ call this $\mathbf{X}_\alpha$ call this $\mathbf{X}_\beta$ call this $\mathbf{X}_\gamma$

Define:

$$\mathbf{X}_\mu = \mathbf{X}_\mu \qquad P_\mu = \mathbf{X}_\mu(\mathbf{X}_\mu^T\mathbf{X}_\mu)^{-1}\mathbf{X}_\mu^T$$

$$\mathbf{X}_{\mu,\alpha} = [\mathbf{X}_\mu|\mathbf{X}_\alpha] \qquad P_{\mu,\alpha} = \mathbf{X}_{\mu,\alpha}(\mathbf{X}_{\mu,\alpha}^T\mathbf{X}_{\mu,\alpha})^{-}\mathbf{X}_{\mu,\alpha}^T$$

$$\mathbf{X}_{\mu,\alpha,\beta} = [\mathbf{X}_\mu|\mathbf{X}_\alpha|\mathbf{X}_\beta] \quad P_{\mu,\alpha,\beta} = \mathbf{X}_{\mu,\alpha,\beta}\left(\mathbf{X}_{\mu,\alpha,\beta}^T\mathbf{X}_{\mu,\alpha,\beta}\right)^{-}\mathbf{X}_{\mu,\alpha,\beta}^T$$

$$\mathbf{X} = [\mathbf{X}_\mu|\mathbf{X}_\alpha|\mathbf{X}_\beta|\mathbf{X}_\gamma] \quad P_\mathbf{X} = \mathbf{X}(\mathbf{X}^T\mathbf{X})^{-}\mathbf{X}^T$$

The following three model matrices correspond to reparameterizations of the same model:

Mode1 1:

$$\begin{bmatrix} 1&1&0&1&0&0&1&0&0&0&0&0\\ 1&1&0&1&0&0&1&0&0&0&0&0\\ 1&1&0&1&0&0&1&0&0&0&0&0\\ 1&1&0&0&1&0&0&1&0&0&0&0\\ 1&1&0&0&1&0&0&1&0&0&0&0\\ 1&1&0&0&0&1&0&0&1&0&0&0\\ 1&1&0&0&0&1&0&0&1&0&0&0\\ 1&0&1&1&0&0&0&0&0&1&0&0\\ 1&0&1&1&0&0&0&0&0&1&0&0\\ 1&0&1&1&0&0&0&0&0&1&0&0\\ 1&0&1&1&0&0&0&0&0&1&0&0\\ 1&0&1&0&1&0&0&0&0&0&1&0\\ 1&0&1&0&0&1&0&0&0&0&0&1\\ 1&0&1&0&0&1&0&0&0&0&0&1\\ 1&0&1&0&0&1&0&0&0&0&0&1 \end{bmatrix} \begin{bmatrix} \mu\\ \alpha_1\\ \alpha_2\\ \beta_1\\ \beta_2\\ \beta_3\\ \gamma_{11}\\ \gamma_{12}\\ \gamma_{13}\\ \gamma_{21}\\ \gamma_{22}\\ \gamma_{23} \end{bmatrix}$$

Model 2:	Model 3:
$\left[\begin{array}{c\|ccccc} 1&1&1&0&1&0\\ 1&1&1&0&1&0\\ 1&1&1&0&1&0\\ 1&1&0&1&0&1\\ 1&1&0&1&0&1\\ 1&1&0&0&0&0\\ 1&1&0&0&0&0\\ 1&0&1&0&0&0\\ 1&0&1&0&0&0\\ 1&0&1&0&0&0\\ 1&0&1&0&0&0\\ 1&0&0&1&0&0\\ 1&0&0&0&0&0\\ 1&0&0&0&0&0\\ 1&0&0&0&0&0 \end{array}\right] \begin{bmatrix} \mu\\ \alpha_1\\ \beta_1\\ \beta_2\\ \gamma_{11}\\ \gamma_{12} \end{bmatrix}$	$\left[\begin{array}{c\|ccccc} 1&1&1&0&1&0\\ 1&1&1&0&1&0\\ 1&1&1&0&1&0\\ 1&1&0&1&0&1\\ 1&1&0&1&0&1\\ 1&1&-1&-1&-1&-1\\ 1&1&-1&-1&-1&-1\\ 1&-1&1&0&-1&0\\ 1&-1&0&1&-1&0\\ 1&-1&1&0&-1&0\\ 1&-1&1&0&-1&0\\ 1&-1&0&1&0&-1\\ 1&-1&-1&-1&1&1\\ 1&-1&-1&-1&1&1\\ 1&-1&-1&-1&1&1 \end{array}\right] \begin{bmatrix} \omega\\ \gamma_1\\ \delta_1\\ \delta_2\\ \eta_{11}\\ \eta_{12} \end{bmatrix}$

$R(\mu) = \mathbf{y}^T P_\mu \mathbf{y}$ is the same for all three model
$R(\mu, \boldsymbol{\alpha}) = \mathbf{y}^T P_{\mu,\alpha}\mathbf{y}$ is the same for all thre
models and so is $R(\alpha|\mu) = R(\mu, \boldsymbol{\alpha}) - R(\mu)$
$R(\mu, \boldsymbol{\alpha}, \boldsymbol{\beta}) = \mathbf{y}^T P_{\mu,\alpha,\beta}\mathbf{y}$ is the same for all thre
models and so is $R(\beta|\boldsymbol{\alpha}) = R(\mu, \boldsymbol{\alpha}, \boldsymbol{\beta}) - R(\mu,$
$R(\mu, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}) = \mathbf{y}^T P_\mathbf{X}\mathbf{y}$ is the same for all thre
models and so is $R(\gamma|\mu, \boldsymbol{\alpha}, \boldsymbol{\beta}) = R(\mu, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma})$ -
$R(\mu, \boldsymbol{\alpha}, \boldsymbol{\beta})$

Consequently, the partition

$$\begin{aligned}\mathbf{y}^T\mathbf{y} &= \mathbf{y}^T P_\mu \mathbf{y} + \mathbf{y}^T(P_{\mu,\beta} - P_\mu)\mathbf{y} \\ &\quad + \mathbf{y}^T(P_{\mu,\alpha,\beta} - P_{\mu,\beta})\mathbf{y} \\ &\quad + \mathbf{y}^T(P_{\mathbf{X}} - P_{\mu,\alpha,\beta})\mathbf{y} \\ &\quad + \mathbf{y}^T(I - P_{\mathbf{X}})\mathbf{y} \\ &= R(\mu) + R(\boldsymbol{\beta}|\mu) + R(\boldsymbol{\alpha}|\mu,\boldsymbol{\beta}) \\ &\quad + R(\boldsymbol{\gamma}|\mu,\alpha,\beta) + SSE\end{aligned}$$

is the same for all three models.

By Cochran's Theorem, these quadratic forms (or sums of squares) have independent chi-square distributions with 1, $b-1$, $a-1$, $(a-1)(b-1)$, and $n_{\bullet\bullet} - ab$ degrees of freedom, respectively, when $n_{ij} > 0$ for all (i,j).

We have also shown earlier that

$$\begin{aligned}SSE &= \mathbf{y}^T(I - P_{\mathbf{X}})\mathbf{y} \\ &= \sum_{i=1}^{a}\sum_{j=1}^{b}\sum_{k=1}^{n_{ij}}(y_{ijk} - \bar{y}_{ij\bullet})^2 \\ &\sim \chi^2_{n_{\bullet\bullet}-ab}\end{aligned}$$

Example 2.

Let $\mathbf{Y} \sim N(\mathbf{W}\boldsymbol{\gamma}, \sigma^2 I)$, where

- $\mathbf{W} = \begin{bmatrix}\mathbf{W_1} & \mathbf{W_2} & \mathbf{W_3} & \mathbf{W_4}\end{bmatrix}$,
- $\mathbf{W_1} = \mathbf{1_{20}}$,
- $\mathbf{W_2} = \begin{bmatrix} 1 \\ -1 \end{bmatrix} \otimes \mathbf{1_{10}}$,
- $\mathbf{W_3} = \mathbf{1_2} \otimes \begin{bmatrix} 1 \\ -1 \end{bmatrix} \otimes \mathbf{1_5}$,
- $\mathbf{W_4} = \mathbf{1_4} \otimes \begin{bmatrix} -8 \\ -4 \\ 0 \\ 8 \\ 4 \end{bmatrix}$, and
- $\boldsymbol{\gamma} = \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \gamma_4 \end{bmatrix}$

(a) Use Cochran's theorem to find the distributions of

- $\frac{1}{\sigma^2}SSE = \mathbf{e^T e} = \mathbf{Y^T(I - P_W)Y}$, where $\mathbf{P_W} = \mathbf{W(W^TW)^{-1}W^T}$
- $\frac{1}{\sigma^2}R(\gamma_1) = \mathbf{Y^T P_{W_1} Y}$ where $\mathbf{W_1} = \mathbf{1}$ is the first column
  $\mathbf{W}$ and
  $\mathbf{P_{W_1}} = \mathbf{W_1(W_1^T W)^{-1} W_1^T}$.
- $\frac{1}{\sigma^2}R(\gamma_2|\gamma_1) = \mathbf{Y^T(P_{W_2} - P_{W_1})}Y$ where $\mathbf{W_2}$ contains t
  first two columns of $\mathbf{W}$ and $\mathbf{P_{W_2}} = \mathbf{W_2(W_2^T W_2)^{-1} W_2^T}$.
- $\frac{1}{\sigma^2}R(\gamma_3|\gamma_1\gamma_2) = \mathbf{Y^T(P_{W_3} - P_{W_2})Y}$. where $\mathbf{W_3}$ contains t
  first three columns of $\mathbf{W}$ and $\mathbf{P_{W_3}} = \mathbf{W_3(W_3^T W_3)^{-1} W_3^T}$
- $\frac{1}{\sigma^2}R(\gamma_4|\gamma_1\gamma_2\gamma_3) = \mathbf{Y^T(P_W - P_{W_3})Y}$.

(b) Report a formula for the non-centrality parameter of the non-central F distribution of

$$F = \frac{R(\gamma_3|\gamma_1, \gamma_2)}{SSE/7}$$

Use it to the null and alternative hypotheses associated with this test statistic. You are given that:

$$\mathbf{W^T}(\mathbf{P_{W_3}} - \mathbf{P_{W_2}})\mathbf{W}] = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 20 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}.$$

5.3.2 Type I Sum of Squares

What null hypotheses are tested by F-tests derived from such ANOVA tables

$R(\mu)$=

For the carrot seed germination study:

$$
\begin{aligned}
P_{\mathbf{1}}\mathbf{X}\boldsymbol{\beta} &= \frac{1}{n_{..}}\mathbf{1}\,\mathbf{1}^T\mathbf{X}\boldsymbol{\beta} \\
&= \frac{1}{n_{..}}\mathbf{1}[n_{..}, n_{1.}, n_{2.}, n_{.1}, n_{.2}, n_{.3}, \\
&\quad n_{11}, n_{12}, n_{13}, n_{21}, n_{22}, n_{23}]\boldsymbol{\beta} \\
&= \frac{1}{n_{..}}\,\mathbf{1}\left(n_{..}\mu + \sum_{i=1}^{a} n_{i.}\alpha_i + \sum_{j=1}^{b} n_{.j}\beta_j \right.\\
&\quad \left. + \sum_{i=1}^{a}\sum_{j=1}^{b}\gamma_{ij}\right)
\end{aligned}
$$

The null hypothesis is

$$H_0 : n_{..}\,\mu + \sum_{i=1}^{a} n_{i.}\,\alpha_i + \sum_{j=1}^{b} n_{.j}\,\beta_j + \sum_{i}\sum_{j} n_{ij}\gamma_{ij} = 0$$

With respect to the cell means

$$E(y_{ijk}) = \mu_{ij} = \mu + \alpha_i + \beta_j + \gamma_{ij}$$

this null hypothesis is

$$H_0 : \sum_{i=1}^{a}\sum_{j=1}^{b}\frac{n_{ij}}{n_{..}}\mu_{ij} = 0$$

Consider

$R(\boldsymbol{\alpha}|\mu) =$

For the general effects model for the carrot seed germination study:

$$P_{\mu,\alpha}\mathbf{X} = \mathbf{X}_{\mu,\alpha}(\mathbf{X}^T_{\mu,\alpha}\mathbf{X}_{\mu,\alpha})^{-}\mathbf{X}^T_{\mu,\alpha}\mathbf{X}$$

$$= \mathbf{X}_{\mu,\alpha}\begin{bmatrix} n_{..} & n_{1.} & n_{2.} \\ n_{1.} & n_{1.} & 0 \\ n_{2.} & 0 & n_{2.} \end{bmatrix}^{-}$$

$$\times \begin{bmatrix} n_{..} & n_{1.} & n_{2.} & n_{.1} & n_{.2} & n_{.3} & n_{11} & n_{12} & n_{13} & n_{21} & n_{22} & n_{23} \\ n_{1.} & n_{1.} & 0 & n_{11} & n_{12} & n_{13} & n_{11} & n_{12} & n_{13} & 0 & 0 & 0 \\ n_{2.} & 0 & n_{2.} & n_{21} & n_{22} & n_{23} & 0 & 0 & 0 & n_{21} & n_{22} & n_{23} \end{bmatrix}$$

$$\downarrow$$

$$= \mathbf{X}_{\mu,\alpha}\begin{bmatrix} 0 & 0 & 0 \\ 0 & \frac{1}{n_{1.}} & 0 \\ 0 & 0 & \frac{1}{n_{2.}} \end{bmatrix}\begin{bmatrix} \quad \end{bmatrix} =$$

$$\begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 0 \\ \vdots & \vdots & \vdots \\ 1 & 1 & 0 \\ 1 & 0 & 1 \\ \vdots & \vdots & \vdots \\ 1 & 0 & 1 \end{bmatrix}\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & \frac{n_{11}}{n_{1.}} & \frac{n_{12}}{n_{1.}} & \frac{n_{13}}{n_{1.}} & \frac{n_{11}}{n_{..}} & \frac{n_{12}}{n_{..}} & \frac{n_{13}}{n_{..}} & 0 & 0 & 0 \\ 1 & 0 & 1 & \frac{n_{11}}{n_{1.}} & \frac{n_{22}}{n_{2.}} & \frac{n_{23}}{n_{2.}} & 0 & 0 & 0 & \frac{n_{21}}{n_{1.}} & \frac{n_{22}}{n_{2.}} & \frac{n_{23}}{n_{1.}} \end{bmatrix}$$

Then, the first seven rows of $(\mathbf{P}_{\mu,\alpha} - \mathbf{P}_{\mu})\mathbf{X}\boldsymbol{\beta}$ ar

$$\left[\mu + \alpha_1 + \textstyle\sum_{j=1}^{b}\frac{n_{1j}}{n_{1.}}(\beta_j + \gamma_{1j})\right]$$

$$-\left[\mu + \sum_{i=1}^{a}\frac{n_{i.}}{n_{..}}\alpha_i + \sum_{j=1}^{b}\frac{n_{.j}}{n_{..}}\beta_j + \sum_{i}\sum_{j}\frac{n}{n}\right.$$

The last eight rows of $(P_{\mu,\alpha} - P_{\mu})\mathbf{X}\boldsymbol{\beta}$ are

$$\left[\mu + \alpha_2 + \textstyle\sum_{j=1}^{b}\frac{n_{2j}}{n_{2.}}(\beta_j + \gamma_{2j})\right]$$

$$-\left[\mu + \sum_{i=1}^{a}\frac{n_{i.}}{n_{..}}\alpha_i + \sum_{j=1}^{b}\frac{n_{.j}}{n_{..}}\beta_j + \sum_{i}\sum_{j}\frac{n}{n}\right.$$

The null hypothesis is

$$H_0 : \alpha_i + \sum_{j=1}^{b}\frac{n_{ij}}{n_{i.}}(\beta_j + \gamma_{ij})$$

are all equal $(i = 1, \ldots, a)$

Consider $R(\boldsymbol{\beta}|\boldsymbol{\mu}, \boldsymbol{\alpha}) = \mathbf{y}^T(P_{\mu,\alpha,\beta} - P_{\mu,\alpha})\mathbf{y}$

and the corresponding F-statistic

$$F = \frac{R(\boldsymbol{\beta}|\mu, \boldsymbol{\alpha})/(b-1)}{MSE} \sim F_{(b-1, n_{..}-ab)}(\lambda)$$

Here,

$$\frac{1}{\sigma^2}R(\boldsymbol{\beta}|\boldsymbol{\mu}, \boldsymbol{\alpha}) \sim \chi^2_{\text{rank}(\mathbf{X}_{\mu,\alpha,\beta}) - \text{rank}(\mathbf{X}_{\mu,\alpha})}(\lambda)$$

$$[1+(a-1)+(b-1)]-[1+(a-1)]$$
$$= b-1 \text{ degrees of freedom}$$

and

$$\lambda = \frac{1}{\sigma^2}\Big[(P_{\mu,\alpha,\beta} - P_{\mu,\alpha})\mathbf{X}\boldsymbol{\beta}\Big]^T\Big[(P_{\mu,\alpha,\beta} - P_{\mu,\alpha})\mathbf{X}\boldsymbol{\beta}\Big]$$

$$P_{\mu,\alpha,\beta}\mathbf{X} = \mathbf{X}_{\mu,\alpha,\beta}\Big[\mathbf{X}^T_{\mu,\alpha,\beta}\mathbf{X}_{\mu,\alpha,\beta}\Big]^{-}\mathbf{X}^T_{\mu,\alpha,\beta}\mathbf{X}$$

$$= \mathbf{X}_{\mu,\alpha,\beta}\left[\begin{array}{c|cc|ccc} n_{..} & n_{1.} & n_{2.} & n_{.1} & n_{.2} & n_{.3} \\ \hline n_{1.} & n_{1.} & 0 & n_{11} & n_{12} & n_{13} \\ n_{2.} & 0 & n_{2.} & n_{21} & n_{22} & n_{23} \\ \hline n_{.1} & n_{11} & n_{21} & n_{.1} & 0 & 0 \\ n_{.2} & n_{12} & n_{22} & 0 & n_{.2} & 0 \\ n_{.3} & n_{13} & n_{23} & 0 & 0 & n_{.3} \end{array}\right]^{-} \mathbf{X}$$

call this $\begin{bmatrix} A & B \\ B^T & C \end{bmatrix}$

$$\begin{bmatrix} A & B \\ B^T & C \end{bmatrix}^{-1} = \begin{bmatrix} A^{-1} & 0 \\ 0 & 0 \end{bmatrix} + \begin{bmatrix} A^{-1}B \\ I \end{bmatrix}[C - B^TA^{-1}B]^{-1}[-B^TA$$

$$= \begin{bmatrix} 0 & 0 \\ 0 & C^{-1} \end{bmatrix} + \begin{bmatrix} I \\ -C^{-1}B^T \end{bmatrix}[A - BC^{-1}B^T]^{-1}[I \mid$$

$$= \begin{bmatrix} W & -WBC^{-1} \\ -C^{-1}B^TW & C^{-1} + C^{-1}B^TWBC^{-1} \end{bmatrix}$$

where $W = [A - BC^{-1}B^T]^{-1}$

The null hypothesis is

$$H_0: \sum_{i=1}^{a} \frac{n_{ij}}{n_{.j}} (\beta_j + \gamma_{ij}) - \sum_{i=1}^{a} \frac{n_{ij}}{n_{.j}} \left(\sum_{k=1}^{b} \frac{n_{ik}}{n_{i.}} (\beta_k + \gamma_{ik}) \right) = 0 \quad \text{for all } j = 1, \ldots, b$$

With respect to the cell means,

$$E(y_{ijk}) = \mu_{ij},$$

this null hypothesis is

$$H_0: \sum_{i=1}^{a} \frac{n_{ij}}{n_{.j}} \mu_{ij} - \sum_{i=1}^{a} \frac{n_{ij}}{n_{.j}} \left(\sum_{k=1}^{b} \frac{n_{ik}}{n_{i.}} \mu_{ik} \right) = 0 \quad \text{for all } j = 1, 2, \ldots, b.$$

Consider

$$R(\boldsymbol{\gamma}|\mu, \boldsymbol{\alpha}, \boldsymbol{\beta}) = \mathbf{y}^T [P_{\mathbf{X}} - P_{\mu,\alpha,\beta}]\mathbf{y}$$

and the associated F-statistic

$$F = \frac{R(\boldsymbol{\gamma}|\mu, \boldsymbol{\alpha}, \boldsymbol{\beta})/[(a-1)(b-1)]}{MSE} \sim F_{(a-1)(b-1), n_{..}-ab}(\lambda)$$

The null hypothesis is:

$$H_0: (\mu_{ij} - \mu_{i\ell} - \mu_{kj} + \mu_{k\ell}) = (\gamma_{ij} - \gamma_{i\ell} - \gamma_{kj} + \gamma_{k\ell}) = 0$$

for all (i, j) and (k, ℓ) .

ANOVA Summary:

Sums of Squares	Associated null hypothesis
$R(\mu)$	$H_0 : \mu + \sum_{i=1}^{a} \frac{n_{i.}}{n_{..}}\alpha_i + \sum_{j=1}^{b} \frac{n_{.j}}{n_{..}}\beta_j + \sum_{i=1}^{a}\sum_{j=1}^{b} \frac{n_{ij}}{n_{..}}\gamma_{ij} = 0$ $\left(\text{or } H_0 : \sum_{i=1}^{a}\sum_{j=1}^{b} \frac{n_{ij}}{n_{..}}\mu_{ij} = 0\right)$
$R(\boldsymbol{\alpha}\|\mu)$	$H_0 : \alpha_i + \sum_{j=1}^{b} \frac{n_{ij}}{n_{i.}}(\beta_j + \gamma_{ij})$ are equal $\left(\text{or } H_0 : \sum_{j=1}^{b} \frac{n_{ij}}{n_{i.}}\mu_{ij} \text{ are equal}\right)$
$R(\boldsymbol{\beta}\|\mu, \boldsymbol{\alpha})$	$H_0 : \beta_j + \sum_{i=1}^{a} \frac{n_{ij}}{n_{.j}}\gamma_{ij} = \sum_{i=1}^{a} \frac{n_{ij}}{n_{.j}} \sum_{k=1}^{b} \frac{n_{ik}}{n_{k.}}(\beta_k + \gamma_{ik})$ for all $j = 1, \ldots, b$ $\left(\text{or } H_0 : \sum_{i=1}^{a} \frac{n_{ij}}{n_{.j}}\mu_{ij} = \sum_{i=1}^{a} \frac{n_{ij}}{n_{.j}} \sum_{k=1}^{b} \frac{n_{ik}}{n_{i.}}\mu_{ik} \text{ for all } j = 1, \ldots, b\right)$
$R(\boldsymbol{\gamma}\|\mu, \boldsymbol{\alpha}, \boldsymbol{\beta})$	$H_0 : \gamma_{ij} - \gamma_{kj} - \gamma_{i\ell} + \gamma_{k\ell} = 0$ for all (i, j) and (k, ℓ) (or $H_0 : \mu_{ij} - \mu_{kj} - \mu_{i\ell} + \mu_{k\ell} = 0$ for all $(i, j)$and (k, ℓ)

Sums of Squares	Associated null hypothesis
$R(\mu)$	$H_0 : \mu + \sum_{i=1}^{a} \frac{n_{i.}}{n_{..}}\alpha_i + \sum_{j=1}^{b} \frac{n_{.j}}{n_{..}}\beta_j + \sum_{i=1}^{a}\sum_{j=1}^{b} \frac{n_{ij}}{n_{..}}\gamma_{ij} = 0$ $\left(\text{or } H_0 : \sum_{i=1}^{a}\sum_{j=1}^{b} \frac{n_{ij}}{n_{..}}\mu_{ij} = 0\right)$
$R(\boldsymbol{\beta}\|\mu)$	$H_0 : \beta_j + \sum_{i=1}^{a} \frac{n_{ij}}{n_{.j}}(\alpha_j + \gamma_{ij})$ are equal for all $j = 1, \ldots, b$ $\left(\text{or } H_0 : \sum_{i=1}^{a} \frac{n_{ij}}{n_{.j}}\mu_{ij} \text{ are equal for all } j = 1, \ldots, b\right)$
$R(\boldsymbol{\alpha}\|\mu, \boldsymbol{\beta})$	$H_0 : \sum_{j=1}^{b} \frac{n_{ij}}{n_{i.}}(\alpha_{ij} + \gamma_{ij}) = \sum_{j=1}^{b} \frac{n_{ij}}{n_{i.}} \sum_{k=1}^{a} \frac{n_{kj}}{n_{.j}}(\alpha_k + \gamma_{kj})$ for all $i = 1, \ldots, a$ $\left(\text{or } H_0 : \sum_{j=1}^{b} \frac{n_{ij}}{n_{i.}}\mu_{ij} = \sum_{j=1}^{b} \frac{n_{ij}}{n_{i.}} \left[\sum_{k=1}^{a} \frac{n_{kj}}{n_{.j}}\mu_{kj}\right] \text{ for all } i = 1, \ldots, a\right)$
$R(\boldsymbol{\gamma}\|\mu, \boldsymbol{\alpha}, \boldsymbol{\beta})$	$H_0 : \gamma_{ij} - \gamma_{kj} - \gamma_{i\ell} + \gamma_{k\ell} = 0$ for all (i, j) and (k, ℓ) $\left(\text{or } H_0 : \mu_{ij} - \mu_{kj} - \mu_{i\ell} + \mu_{k\ell} = 0 \text{ for all } (i, j) \text{ and } (k, \ell)\right)$

Soil Tpye	Variety 1	2	3
1	$y_{111} = 6$	$y_{121} = 13$	$y_{131} = 14$
	$y_{112} = 10$	$y_{122} = 15$	$y_{132} = 22$
	$y_{113} = 11$		
2	$y_{211} = 12$	$y_{221} = 31$	$y_{231} = 18$
	$y_{212} = 15$		$y_{232} = 9$
	$y_{213} = 19$		$y_{233} = 12$
	$y_{214} = 18$		

Type I sums of squares

```
R-Codes
#Type I Sum of Squares(A follows by B)
Y = c(6, 10, 11, 13,15,14,22,12,15,19,18,31,18,9,12)
xmu = rep(1,15)
xa1 = c(rep(1,7),rep(0,8))
xa2 = 1-xa1
xalpha = cbind(xa1, xa2)
xb1 = c(rep(1,3), rep(0,4), rep(1,4), rep(0,4))
xb2 = c(rep(0,3), rep(1,2), rep(0,6), 1, rep(0,3))
xb3 = c(rep(0,5), 1,1, rep(0,5),rep(1,3))
xbeta = cbind(xb1,xb2,xb3)
xab11 = xa1*xb1
xab12 = xa1*xb2
xab13 = xa1*xb3
xab21 = xa2*xb1
xab22 = xa2*xb2
```



```
xab23 = xa2*xb3
xgamma = cbind(xab11,xab12,xab13,xab21,xab22,xab23)
library(MASS)
Pmu = xmu%*%solve(t(xmu)%*%xmu)%*%t(xmu)
xma = cbind(xmu, xalpha)
Pma = xma%*%ginv(t(xma)%*%xma)%*%t(xma)
xmab = cbind(xmu, xalpha, xbeta)
Pmab = xmab%*%ginv(t(xmab)%*%xmab)%*%t(xmab)
X = cbind(xmu, xalpha, xbeta, xgamma)
PX = X%*%ginv(t(X)%*%X)%*%t(X)
In = diag(rep(1,15))
A1 = Pmu
A2 = Pma - Pmu
A3 = Pmab - Pma
A4 = PX - Pmab
A5 = In - PX
Rmu = t(Y)%*%A1%*%Y
Rma = t(Y)%*%A2%*%Y
Rma
Rmab = t(Y)%*%A3%*%Y
Rmabg =  t(Y)%*%A4%*%Y
SSE = t(Y)%*%A5%*%Y
MRmu = Rmu
MRma = Rma
MRmab = Rmab/2
MRmabg = Rmabg/2
MSE = SSE/9
Fmu = MRmu/MSE
Fa = MRma/MSE
Fb = MRmab/MSE
Fab = MRmabg/MSE
PVmu = 1-pf(Fmu,1,9)
PVa = 1-pf(Fa,1,9)
PVb = 1-pf(Fb,2,9)
PVab = 1-pf(Fab,1,9)
data.frame(Source = "Intercept", SS=Rmu, df = 1, MS = MRmu, F.S
```

```
p.value = PVmu)
data.frame(Source = "Soil",SS=Rma, df = 1, MS = MRma, F.Stat = Fa,
p.value = PVa)
data.frame(Source = "Variety",SS=Rmab, df = 2, MS = MRmab, F.Stat = Fb,
p.value = PVb)
data.frame(Source = "Interaction",SS=Rmabg, df = 2, F.Stat = Fab,
p.value = PVab)
data.frame(Source = "Error",SS=SSE, df = 9,MS = MSE)
#---------------------------------------
#Using lm() function
Y = c(6, 10, 11, 13,15,14,22,12,15,19,18,31,18,9,12)
FA = as.factor(c(1,1,1,1,1,1,1,2,2,2,2,2,2,2,2))
FB = as.factor(c(1,1,1,2,2,3,3,1,1,1,1,2,3,3,3))
mod.fit = lm(Y ~ FA*FB)
anova(mod.fit)
```

Source of variat.	d.f.	sums of squares	Mean square	F	p-value
"Soils"	$a-1=1$	$R(\boldsymbol{\alpha}\|\boldsymbol{\mu})=52.50$	52.5	3.94	.0785
"Var."	$b-1=2$	$R(\boldsymbol{\beta}\|\mu,\boldsymbol{\alpha})=124.73$	62.4	4.68	.0405
Inter-action	(a-1)(b-1) -2	$R(\boldsymbol{\gamma}\|\mu,\boldsymbol{\alpha},\boldsymbol{\beta})=222.76$	111.38	8.35	.0089
"Res."	$\Sigma\Sigma(n_{ij}-1)$ =9	$\mathbf{y}^T(I-P_{\mathbf{X}})\mathbf{y}=120.00$	13.33		
Corr. total	$n_{..}-1=14$	$\mathbf{y}^T(I-P_1)\mathbf{y}=520.00$			


```
#Type I Sum of Squares(B follows by A)
Y = c(6, 10, 11, 13,15,14,22,12,15,19,18,31,18,9,12)
xmu = rep(1,15)
xa1 = c(rep(1,7),rep(0,8))
xa2 = 1-xa1
xalpha = cbind(xa1, xa2)
xb1 = c(rep(1,3), rep(0,4), rep(1,4), rep(0,4))
xb2 = c(rep(0,3), rep(1,2), rep(0,6), 1, rep(0,3))
xb3 = c(rep(0,5), 1,1, rep(0,5),rep(1,3))
xbeta = cbind(xb1,xb2,xb3)
xab11 = xa1*xb1
xab12 = xa1*xb2
xab13 = xa1*xb3
xab21 = xa2*xb1
xab22 = xa2*xb2
xab23 = xa2*xb3
xgamma = cbind(xab11,xab12,xab13,xab21,xab22,xab23)
library(MASS)
Pmu = xmu%*%solve(t(xmu)%*%xmu)%*%t(xmu)
xmb = cbind(xmu, xbeta)
Pmb = xmb%*%ginv(t(xmb)%*%xmb)%*%t(xmb)
xmab = cbind(xmu, xalpha, xbeta)
Pmab = xmab%*%ginv(t(xmab)%*%xmab)%*%t(xmab)
X = cbind(xmu, xalpha, xbeta, xgamma)
PX = X%*%ginv(t(X)%*%X)%*%t(X)
In = diag(rep(1,15))
A1 = Pmu
A2 = Pmb - Pmu
A3 = Pmab - Pmb
A4 = PX - Pmab
A5 = In - PX
Rmu = t(Y)%*%A1%*%Y
Rma = t(Y)%*%A2%*%Y
Rma
```

```
Rmab = t(Y)%*%A3%*%Y
Rmabg =  t(Y)%*%A4%*%Y
SSE = t(Y)%*%A5%*%Y
MRmu = Rmu
MRma = Rma
MRmab = Rmab/2
MRmabg = Rmabg/2
MSE = SSE/9
Fmu = MRmu/MSE
Fa = MRma/MSE
Fb = MRmab/MSE
Fab = MRmabg/MSE
PVmu = 1-pf(Fmu,1,9)
PVa = 1-pf(Fa,1,9)
PVb = 1-pf(Fb,2,9)
PVab = 1-pf(Fab,1,9)
data.frame(Source = "Intercept", SS=Rmu, df = 1, MS = MRmu, F.Stat = Fmu,
p.value = PVmu)
data.frame(Source = "Soil",SS=Rma, df = 1, MS = MRma, F.Stat = Fa,
p.value = PVa)
data.frame(Source = "Variety",SS=Rmab, df = 2, MS = MRmab, F.Stat = Fb,
p.value = PVb)
data.frame(Source = "Interaction",SS=Rmabg, df = 2, F.Stat = Fab,
p.value = PVab)
data.frame(Source = "Error",SS=SSE, df = 9,MS = MSE)
```


Source of variat.	d.f.	sums of squares	Mean square	F	p-value
“Var.”	$b-1=2$	$R(\boldsymbol{\beta}\|\mu)=93.33$	46.67	3.50	.0751
“Soils”	$a-1=1$	$R(\alpha\|\boldsymbol{\mu},\boldsymbol{\beta})=83.90$	83.90	6.29	.0334
Inter-action	(a-1)(b-1) =2	$R(\boldsymbol{\gamma}\|\mu,\boldsymbol{\alpha},\boldsymbol{\beta})=222.76$	111.38	8.35	.0089
“Res.”	$\Sigma\Sigma(n_{ij}-1)$ =9	$\mathbf{y}^T(I-P_{\mathbf{X}})\mathbf{y}=120.00$	13.33		
Corr. total	$n_{\cdot\cdot}-1=14$	$\mathbf{y}^T(I-P_{\mathbf{1}})\mathbf{y}=520.00$			

5.3.3 Method of Unweighted Means - Type III Sum of Squares

(Type III sums of squares in when $n_{ij} > 0$ for all (i, j)).

Use the cell means reparameterization of the model:

$$\begin{aligned} y_{ijk} &= \mu + \alpha_i + \beta_j + \gamma_{ij} + \epsilon_{ijk} \\ &= \mu_{ij} + \epsilon_{ijk} \end{aligned}$$

$$\underset{\mathbf{y}}{\begin{bmatrix} y_{111} \\ y_{112} \\ y_{113} \\ y_{121} \\ y_{122} \\ y_{131} \\ y_{132} \\ y_{211} \\ y_{212} \\ y_{213} \\ y_{214} \\ y_{221} \\ y_{231} \\ y_{232} \\ y_{233} \end{bmatrix}} = \underset{D}{\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}} \underset{\boldsymbol{\mu}}{\begin{bmatrix} \mu_{11} \\ \mu_{12} \\ \mu_{13} \\ \mu_{21} \\ \mu_{22} \\ \mu_{23} \end{bmatrix}} + \boldsymbol{\epsilon}$$

The model is

$$\mathbf{y} = D\boldsymbol{\mu} + \boldsymbol{\epsilon}$$

The least squares estimator (b.l.u.e.) for $\boldsymbol{\mu}$ is

Test the hypotheses are:

The OLS estimator (b.l.u.e.) for $\frac{1}{b}\sum_{j=1}^{b}\mu_{ij}$ an

it's variance are

Express the null hypothesis in matrix form:

$$H_0 : C_1\boldsymbol{\mu} = \mathbf{0}$$

Then the OLS estimator (BLUE) of $C_1\boldsymbol{\mu}$, an
it's variance are:

Compute SS_{H_0} and show that

$$\frac{1}{\sigma^2}SS_{H_0} \sim \chi^2_{(a-1)}(\lambda)$$

Compute:
$SSE = \mathbf{y}^T(I-P_D)\mathbf{y}$ where $P_D = D(D^TD)^{-1}$
Show that

$$\frac{1}{\sigma^2}SSE \sim \chi^2_{\Sigma\Sigma(n_{ij}-1)}$$

Show that

$$SSE = \mathbf{y}^T \underbrace{(I - P_D)}_{\nwarrow \text{ call this } A_1}\mathbf{y}$$

is distributed independently of

$$SS_{H_0} = \mathbf{y}^T \underbrace{D(D^TD)^{-1}C_1^T[C_1(D^TD)^{-1}C_1^T]^{-1}C_1(D^TD)^{-1}}_{\nwarrow \text{ call this } A_2}D^T\mathbf{y}$$

Then $F =$

Test

$$H_0 : \frac{1}{a}\sum_{i=1}^{a} \mu_{i1} = \frac{1}{a}\sum_{i=1}^{a} \mu_{i2} = \cdots = \frac{1}{a}\sum_{i=1}^{a} \mu_{ib}$$

vs.

$$H_A : \frac{1}{a}\sum_{i=1}^{a} \mu_{ij} \neq \frac{1}{a}\sum_{i=1}^{a} \mu_{ik} \quad \text{for some } j \neq k$$

Write the null hypothesis in matrix form as

$$H_0 : C_2\boldsymbol{\mu} = \mathbf{0}$$

where $C_2 =$

then $C_2\boldsymbol{\mu} =$

Compute $SS_{H_{0,2}}$ and reject H_0 if $F =$

Test for Interaction:
Test
$H_0 : \mu_{ij} - \mu_{i\ell} - \mu_{kj} + \mu_{k\ell} = 0$ for all (i, j) an
(k, ℓ) vs.
$H_A : \mu_{ij} - \mu_{i\ell} - \mu_{kj} + \mu_{k\ell} \neq 0$ for all (i, k) an
$(j \neq \ell)$.
Write the null hypothesis in matrix form as

$$H_0 : C_3\, \boldsymbol{\mu} = \mathbf{0}$$

and perform the test.

```
#Type III Sum of Squares
Y = c(6,10,11,13,15,14,22,12,15,19,18,31,18,9,12)
Y = c(6,10,11,13,15,14,22,12,15,19,18,31,18,9,12)
d1 = c(rep(1,3), rep(0,12))
d2 = c(0,0,0,1,1,rep(0,10))
d3 = c(rep(0,5),1,1,rep(0,8))
d4 = c(rep(0,7),rep(1,4),rep(0,4))
d5 = c(rep(0,11), 1, rep(0,3))
d6 = c(rep(0,12), 1, 1,1)
D = cbind(d1,d2,d3,d4,d5,d6)
a = 2
b = 3
beta  = solve(t(D)%*%D)%*%t(D)%*%Y
Yhat = D%*%beta
SSE = crossprod(Y-Yhat)
df2 = NROW(Y) - a*b
am1 = a-1
bm1 = b-1
Iam1 = diag(rep(1,am1))
Ibm1 = diag(rep(1,bm1))
Onea = c(rep(1,a))
Oneam1 = c(rep(1,am1))
Oneb = c(rep(1,b))
Onebm1 = c(rep(1,bm1))
C1 = kronecker(cbind(Iam1, -Oneam1),t(Oneb))
C1b = C1%*%beta
SSH0a = t(C1b)%*%
solve(C1%*%solve(crossprod(D))%*%t(C1))%*%C1b
df1 = b-1
```



```
F = (SSH0a/df1)/(SSE/df2)
p = 1-pf(F, df1,df2)
C1
data.frame(SS=SSH0a, df = df1, F.Stat = F, p.value =

C2 = kronecker(t(Onea), cbind(Ibm1, -Onebm1))
C2b = C2%*%beta
SSH0b = t(C2b)%*%
solve(C2%*%solve(crossprod(D))%*%t(C2))%*%C2b
df1 = b-1
F = (SSH0b/df1)/(SSE/df2)
p = 1-pf(F, df1,df2)
C2
data.frame(SS=SSH0b, df = df1, F.Stat = F, p.value =

C3 = kronecker(cbind(Iam1, -Oneam1), cbind(Ibm1, -One
C3b = C3%*%beta
SSH0ab = t(C3b)%*%
solve(C3%*%solve(crossprod(D))%*%t(C3))%*%C3b
df1 = (a-1)*(b-1)
F = (SSH0ab/df1)/(SSE/df2)
p = 1-pf(F, df1,df2)
C3
data.frame(SS=SSH0ab, df = df1, F.Stat = F, p.value =
```

Source of variation	Sum of d.f.	Mean Squares	Square	F	p-value
Soils	a-1=1	$SS_{H_0} =$ 123.77	123.77	9.28	.0139
Var.	b-1=2	$SS_{H_{0,2}} =$ 192.13	96.06	7.20	.0135
Inter.	(a-1)(b-1)=2	$SS_{H_{0,3}} =$ 222.76	111.38	8.35	.0089

Note that

$$\begin{aligned}\mathbf{y}^T P_{\mathbf{1}}\mathbf{y} &+ \mathbf{y}^T D(D^T D)^{-1}[C_1(D^T D)^{-1}C_1^T]^{-1} \\ &\qquad C_1(D^T D)^{-1}D^T\mathbf{y} \\ &+ \mathbf{y}^T D(D^T D)^{-1}C_2^T[C_2(D^T D)^{-1}C_2^T \\ &\qquad C_2(D^T D)^{-1}D^T\mathbf{y} \\ &+ \mathbf{y}^T D(D^T D)^{-1}C_3^T[C_3(D^T D)^{-1}C_3^T \\ &\qquad C_3(D^T D)^{-1}D^T\mathbf{y} \\ &+ \mathbf{y}^T(I - P_D)\mathbf{y}\end{aligned}$$

do not necessarily sum to $\mathbf{y}^T\mathbf{y}$, nor do the mic
dle three terms (SS_{H_0}, $SS_{H_0,2}$, $SS_{H_0,3}$) nece
sarily sum to

$$SS_{\text{model,corrected}} = \mathbf{y}^T(P_D - P_{\mathbf{1}})\mathbf{y} ,$$

nor are (SS_{H_0}, $SS_{H_0,2}$, $SS_{H_0,3}$) necessarily in
dependent of each other.

Example 3.

A chemical production process consists of a first reaction with an alcohol and a second reaction with a base. A 3×2 factorial experiment with three alcohols and two bases was conducted. The data had unequal replications among the six treatment combinations of the two factors, Base and Alcohol. The collected data are percent yield. The data are given below.

	Alcohol		
Base	1	2	3
1	90.0 91.3	89.4 88.1 90.0	90.2 87.9 89.4 91.5
2	87.5 89.4 91.8	96.0	94.1 92.5 92.8

Consider the model $y_{ijk} = \mu_{ij} + \epsilon_{ijk}$, where $\epsilon_{ijk} \sim NID(0, \sigma^2)$, $i = 1, 2$, and $j = 1, 2, 3$ and $k = 1, \ldots, n_{ij}$. This model can be expressed in matrix form as $\mathbf{Y} = \mathbf{D}\boldsymbol{\beta} + \boldsymbol{\epsilon}$. Examine type III sums of squares for these data.

(a) Specify the $\mathbf{C}$ matrix needed to write the nu hypothesis associated with the F-test for A cohol effects in the form $H_0 : \mathbf{C}\boldsymbol{\beta} = \mathbf{0}$.

(b) Present a formula for SS_{H_0} , corresponding to the null hypothesis in part (a), and state it's distribution when the null hypothesis is true.

(c) Compute SS_{H_0}.

5.4 Balanced Factorial Experiments

$$n_{ij} = n \quad \text{for} \quad i = 1, \ldots, a$$
$$j = 1, \ldots, b$$

Example 4. Sugar Cane yields

	Nitrogem Level		
	150 lb/acre	210 lb/acre	270 lb/acre
Variety 1	$y_{111} = 70.5$	$y_{121} = 67.3$	$y_{131} = 79.9$
	$y_{112} = 67.5$	$y_{122} = 75.9$	$y_{132} = 72.8$
	$y_{113} = 63.9$	$y_{123} = 72.2$	$y_{133} = 64.8$
	$y_{114} = 64.2$	$y_{124} = 60.5$	$y_{134} = 86.3$
Variety 2	$y_{211} = 58.6$	$y_{221} = 64.3$	$y_{231} = 64.4$
	$y_{212} = 65.2$	$y_{222} = 48.3$	$y_{232} = 67.3$
	$y_{213} = 70.2$	$y_{223} = 74.0$	$y_{233} = 78.0$
	$y_{214} = 51.8$	$y_{224} = 63.6$	$y_{234} = 72.0$
Variety 3	$y_{311} = 65.8$	$y_{321} = 64.1$	$y_{331} = 56.3$
	$y_{312} = 68.3$	$y_{322} = 64.8$	$y_{332} = 54.7$
	$y_{313} = 72.7$	$y_{323} = 70.9$	$y_{331} = 66.2$
	$y_{314} = 67.6$	$y_{324} = 58.3$	$y_{334} = 54.4$

For a balanced experiment ($n_{ij} = n$), Type Type II, and Type III sums of squares are th same:

$R(\boldsymbol{\alpha}|\mu) =$

$R(\boldsymbol{\beta}|\mu) =$

$R(\boldsymbol{\gamma}|\mu, \boldsymbol{\alpha}, \boldsymbol{\beta}) =$

ANOVA

Sum of Squares	Associated null hypothesis
$R(\mu) = \mathbf{y}^T P_{\mathbf{1}} \mathbf{y}$	$H_0 : \mu + \frac{1}{a}\sum_{i=1}^{a} \alpha_i + \frac{1}{b}\sum_{j=1}^{b} \beta_j$
$= a\,b\,n\,\bar{y}_{...}^2$	$+ \frac{1}{a\,b}\sum_{i=1}^{a}\sum_{j=1}^{b} \gamma_{ij} = 0$
	$\left(H_0 : \frac{1}{a\,b}\sum_{i=1}^{a}\sum_{j=1}^{b} \mu_{ij} = 0 \right)$
$R(\boldsymbol{\alpha}\|\mu) = R(\boldsymbol{\alpha}\|\mu, \boldsymbol{\beta})$	$H_0 : \alpha_i + \frac{1}{b}\sum_{j=1}^{b}(\beta_j + \gamma_{ij})$
$= n\,b \sum_{i=1}^{a} (\bar{y}_{i..} - \bar{y}_{...})^2$	are equal
	$\left(H_0 : \frac{1}{b}\sum_{j=1}^{b} \mu_{ij} \text{ are equal} \right)$
$R(\boldsymbol{\beta}\|\mu) = R(\boldsymbol{\beta}\|\mu, \boldsymbol{\alpha})$	$H_0 : \beta_j + \frac{1}{a}\sum_{i=1}^{a}(\alpha_i + \gamma_{ij})$
$= n\,a \sum_{j=1}^{b} (\bar{y}_{.j.} - \bar{y}_{...})^2$	are equal
	$\left(H_0 : \frac{1}{a}\sum_{i=1}^{a} \mu_{ij} \text{ are equal} \right)$

$$R(\boldsymbol{\gamma}|\mu, \boldsymbol{\alpha}, \boldsymbol{\beta}) = n \sum_{i=1}^{a}\sum_{j=1}^{b} (\bar{y}_{ij.} - \bar{y}_{i..} - \bar{y}_{.j.} + \bar{y}_{...})$$

$$H_0 : \gamma_{ij} - \gamma_{kj} - \gamma_{i\ell} + \gamma_{k\ell} = 0 \quad \text{for all } (i, j) \text{ and } (k, \ell)$$

$$\left(H_0 : \mu_{ij} - \mu_{kj} - \mu_{i\ell} + \mu_{k\ell} = 0 \quad \text{for all } (i, j) \text{ and } (k, \ell) \right)$$